

Multi-Source Deep Domain Adaptation with Weak Supervision for Time-Series Sensor Data

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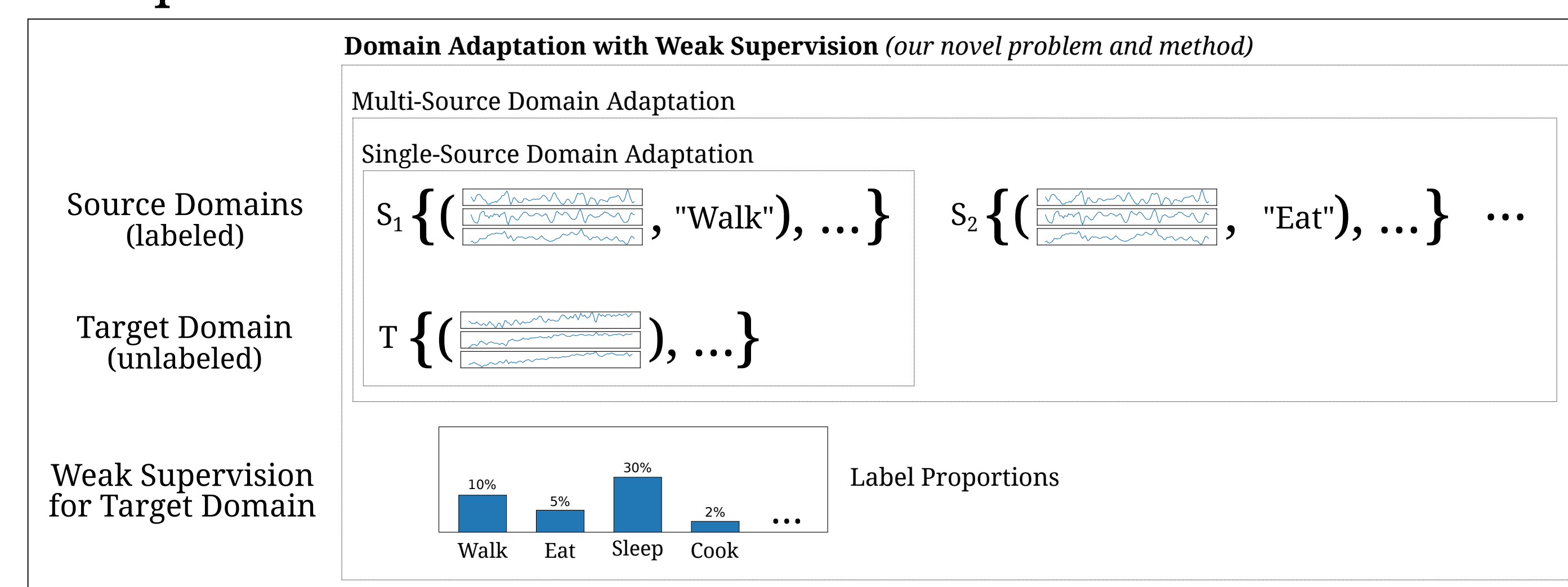
Introduction

Domain adaptation (DA) provides a means to reuse data for new problem domains, but most prior DA methods don't support time series, and those that do lack support for varying amounts of data availability – specifically, multiple source domains and weak supervision.

Contributions

- Improved time-series compatible model
- Domain adversarial adaptation method supporting:
 - Multiple source domains
 - Weak supervision, specifically, target-domain label proportions
- Experimental validation

Adaptation Task



Problem Setup

Multi-Source Domain Adaptation

During training, we have labeled data from n source domains and unlabeled data from a target domain.

$$S_i = \{(\mathbf{x}_j, y_j)\}_{j=1}^{s_i} \sim \mathcal{D}_{S_i}, \quad \forall i \in \{1, 2, \dots, n\}$$

$$T = \{(\mathbf{x}_j)\}_{j=1}^t \sim \mathcal{D}_T^X$$

Domain Adaptation with Weak Supervision

During training, we additionally have target-domain label proportions (e.g. from self-report, in the case of activity recognition), which can be represented as a discrete probability distribution over the L class labels.

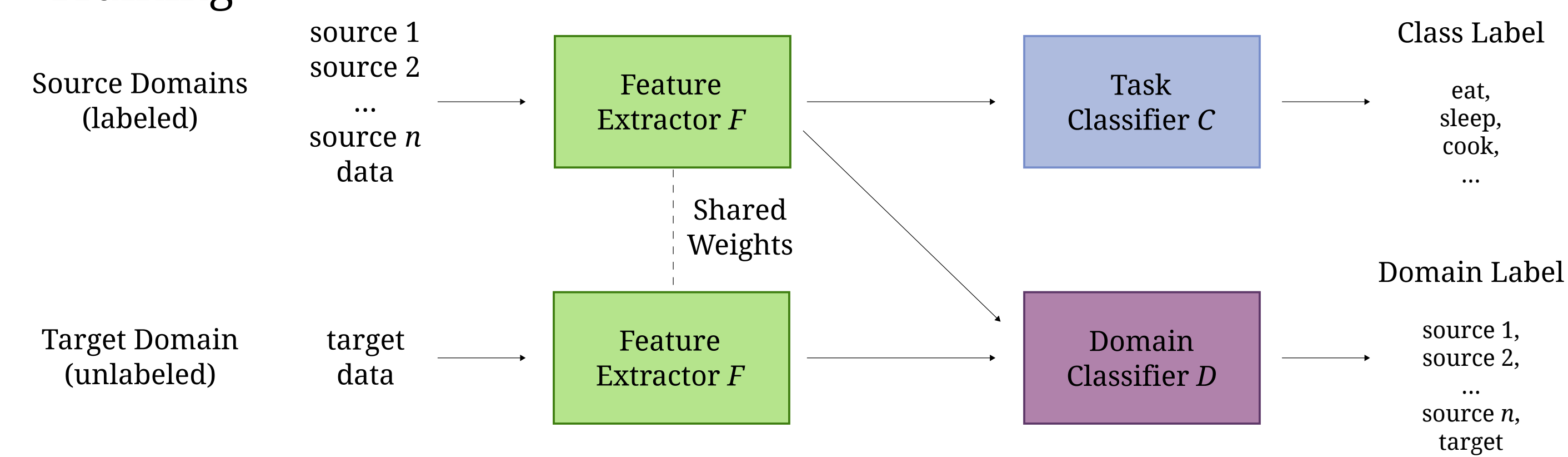
$$Y_{true}(y) = P(Y = y) = p_y, \quad \forall y \in \{1, 2, \dots, L\}$$

Proposed Method

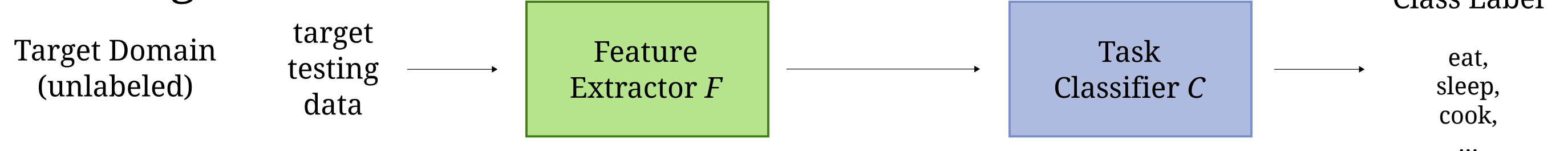
Multi-Source Domain Adaptation

Using domain adversarial training, we train a domain-invariant feature extractor thereby transferring the task classifier to the target domain. Adversarial training is performed by negating the gradient from the domain classifier when updating the feature extractor weights. To support multiple source domains, we use a multinomial domain classifier.

Training



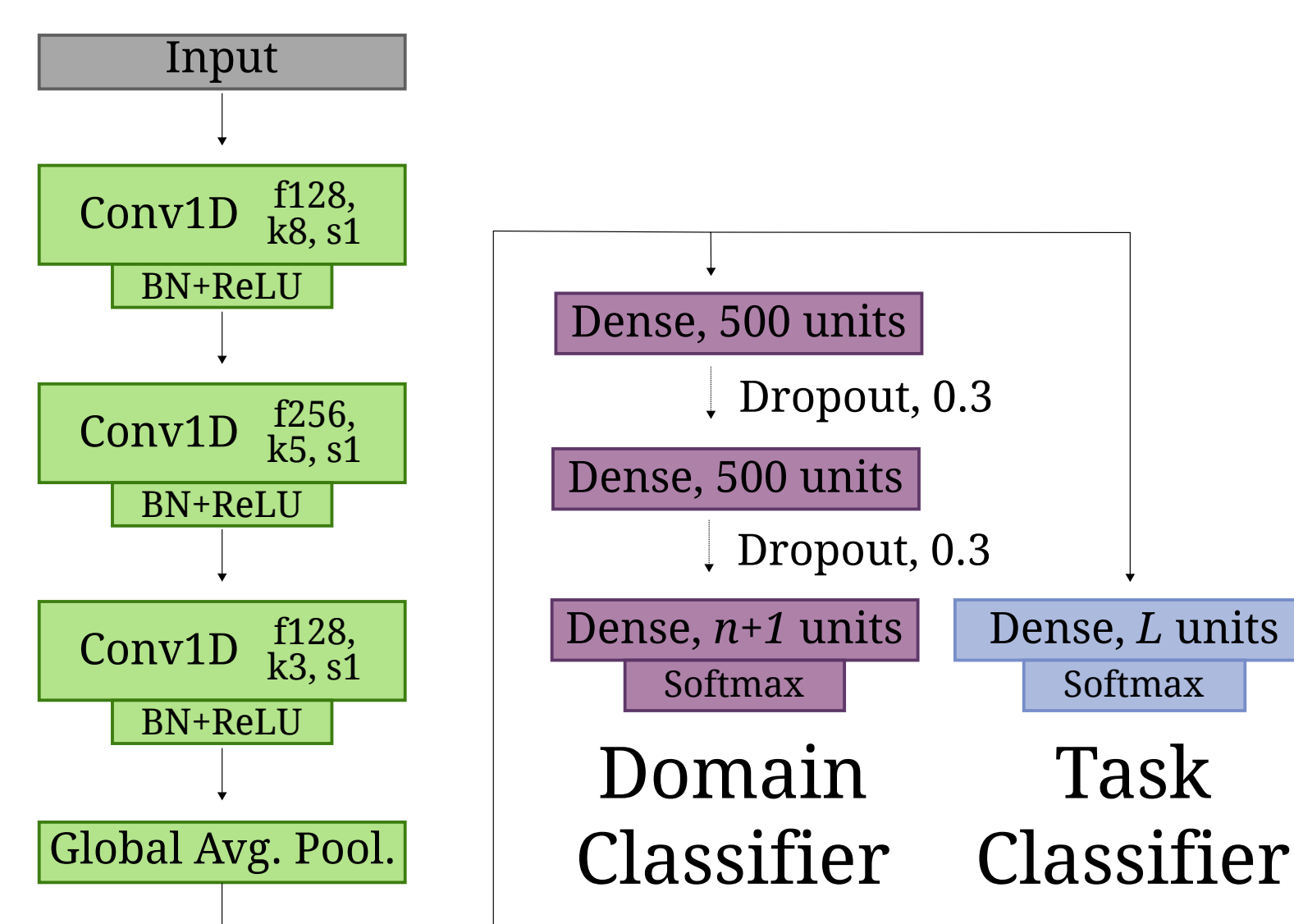
Testing



Model Architecture

We propose using the following time-series compatible network based on 1D convolutions. Variable-length time series can be handled by the global average pooling layer.

Feature Extractor



Domain Adaptation with Weak Supervision

To take advantage of possible class balance differences between the sources domains and the target domain, we add a regularizer to the training objective that constrains the space of model parameters to those approximately matching the target-domain label proportions estimated over a mini-batch.

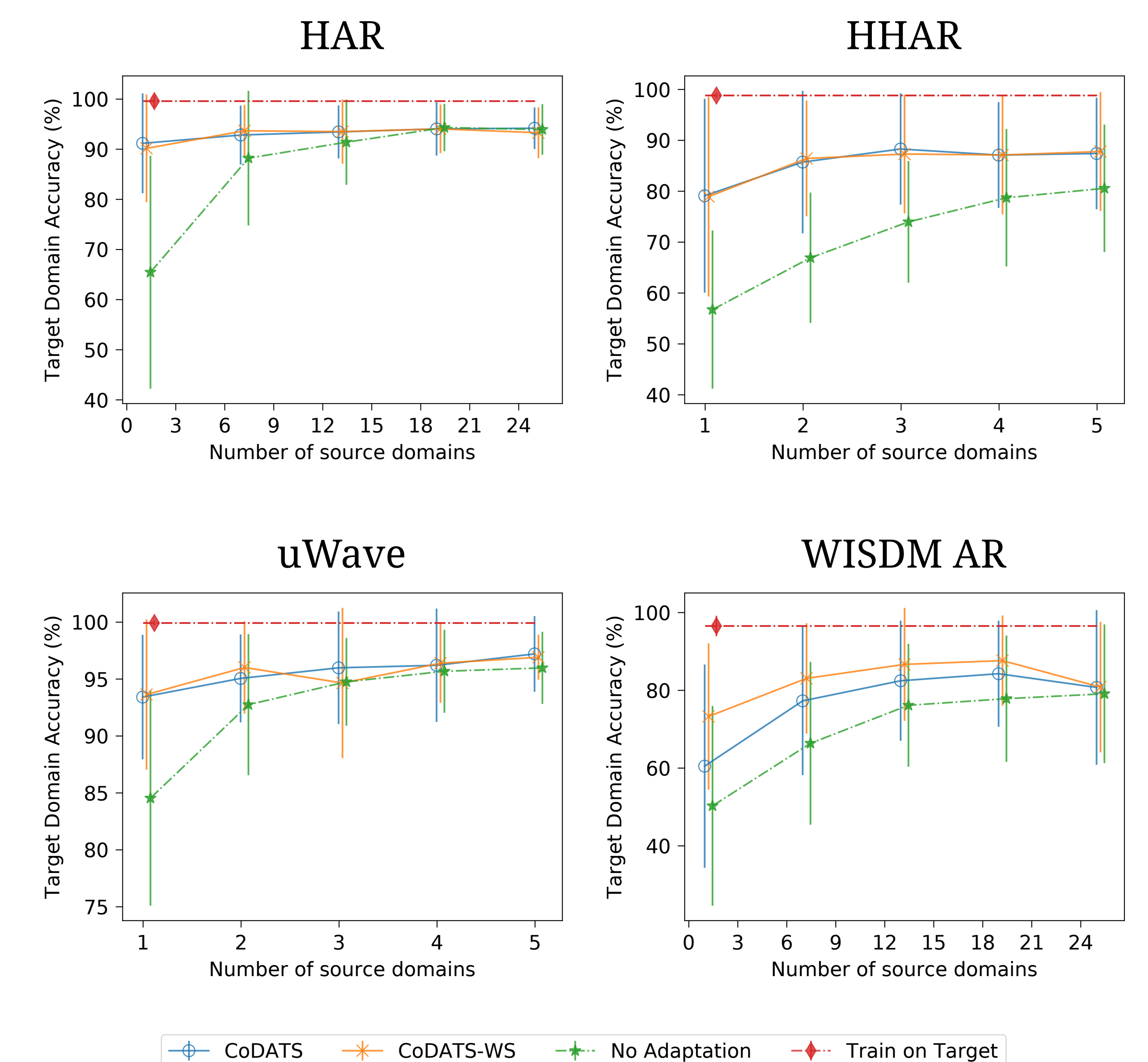
$$\begin{aligned} \mathcal{L}_{WS} &= D_{KL}(Y_{true}(y) \parallel \tilde{Y}_{pred}(y)) \\ &= D_{KL}(Y_{true} \parallel \mathbb{E}_{\mathbf{x} \sim \mathcal{D}_T^X} [C(F(\mathbf{x}))]) \end{aligned}$$

Experimental Results

Below are the single-source results followed by the multi-source results. To see improvements from each part of our proposed method:

- Model - compare CoDATS with prior works R-DANN & VRADA
- Multiple source domains - plot curves increase with more sources
- Weak supervision - compare CoDATS-WS with CoDATS on WISDM AR

Problem	No Adaptation	R-DANN	VRADA	CoDATS	CoDATS-WS	Train on Target
HAR	69.2 ± 21.8	70.2 ± 14.0	70.0 ± 11.4	88.4 ± 10.1	90.2 ± 10.1	100.0 ± 0.0
HHAR	64.8 ± 16.9	68.7 ± 17.6	68.3 ± 16.4	88.3 ± 11.4	86.8 ± 11.8	99.0 ± 0.3
WISDM AR	56.8 ± 21.3	48.3 ± 16.0	61.2 ± 18.9	70.0 ± 11.6	75.8 ± 15.4	98.5 ± 1.6
uWave	91.0 ± 6.5	48.4 ± 15.8	19.7 ± 8.3	94.3 ± 4.6	94.2 ± 2.9	100.0 ± 0.0



Conclusions and Future Work

We introduced CoDATS, which improves over prior time series domain adaptation work by making use of data from multiple source domains, incorporating weak supervision, and using a new DA model architecture.

Future Work

- Extend to support heterogeneous feature sets
- Develop additional forms of weak supervision relevant for time series
- Further model improvements

Acknowledgments: This material is based upon work supported by the National Science Foundation under Grant No. 1543656 and by the National Institutes of Health under Grant No. R01EB009675. This research used resources from the Center for Institutional Research Computing at Washington State University.